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Modeling the impacts of temperature and precipitation changes on soil CO_2 fluxes from a Switchgrass stand recently converted from cropland

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ABSTRACT

Switchgrass (*Panicum virgatum* L.) is a perennial C_4 grass native to North America and successfully adapted to diverse environmental conditions. It offers the potential to reduce soil surface carbon dioxide (CO_2) fluxes and mitigate climate change. However, information on how these CO_2 fluxes respond to changing climate is still lacking. In this study, CO_2 fluxes were monitored continuously from 2011 through 2014 using high frequency measurements from Switchgrass land seeded in 2008 on an experimental site that has been previously used for soybean (*Glycine max* L.) in South Dakota, USA. DAYCENT, a process-based model, was used to simulate CO_2 fluxes. An improved methodology CPTE [Combining Parameter estimation (PEST) with "Trial and Error" method] was used to calibrate DAYCENT. The calibrated DAYCENT model was used for simulating future CO_2 emissions based on different climate change scenarios. This study showed that: (i) the measured soil CO_2 fluxes from Switchgrass land were higher for 2012 which was a drought year, and these fluxes when simulated using DAYCENT for long-term (2015–2070) provided a pattern of polynomial curve; (ii) the simulated CO_2 fluxes provided different patterns with temperature and precipitation changes in a long-term, (iii) the future CO_2 fluxes from Switchgrass land under different changing climate scenarios were not significantly different, therefore, it can be concluded that Switchgrass grown for longer durations could reduce changes in CO_2 fluxes from soil as a result of temperature and precipitation changes to some extent.

Introduction

Switchgrass is a perennial C_4 grass, native to North America and successfully adapted to diverse environmental conditions over large geographic regions (Lewandowski et al., 2003). It was first identified as a renewable energy source by the U.S. Department of Energy in 1985. This perennial grass can be used for livestock forage, soil stabilization, and wildlife cover. Further, Switchgrass

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can be adapted to marginal lands, and tolerates soil water deficits and low soil nutrient concentrations. Therefore, Switchgrass has been extensively evaluated for further development over the last two decades (Parrish and Fike, 2005; Wright, 2007). The current US average Switchgrass yield was projected to double or even triple by 2025 (McLaughlin et al., 2006). However, information regarding growing Switchgrass on marginal lands in the North Central region of USA and how it responds to climate change when grown in a recently converted cropland is lacking.

Mitigation of carbon dioxide (CO_2) emissions to the atmosphere is a key to solve the problem of global warming. It has been well documented in the literature that perennial crops emit less CO_2 emissions than corn (*Zea mays* L.) or soybean (Adler et al., 2007). Therefore, it can be beneficial economically and environmentally to plant Switchgrass on marginally yielding cropland areas over the long-term in order to mitigate the climate change impacts. However, it is very difficult to monitor climate change impacts associated with CO_2 fluxes. Furthermore, monitoring these CO_2 fluxes across the region from all possible combinations of environmental and soil conditions is very difficult (De Gryze et al., 2010). Therefore, process-based ecosystem models provide an option to simulate CO_2 emissions that can account for all possible permutations of management and climate in the region.

DAYCENT model (Parton et al., 1998), the daily version of the CENTURY (Parton, 1996; Parton et al., 1987), was selected in this study. It is a fully resolved ecosystem model simulating major ecosystem processes such as changes in soil organic matter, plant productivity, nutrient cycling (*i.e.*, N, P, and S), CO_2 respiration, soil water, and soil temperature (De Gryze et al., 2010). However, performance of this model strongly depends on how well it is calibrated and validated for the specific environmental conditions being evaluated (De Gryze et al., 2010; Smith et al., 1997). Therefore, calibration of these models is very important in order to assess long-term scenarios. Methods of calibrating DAYCENT used in previous studies (Chamberlain et al., 2011; Davis et al., 2010) were "trial and error" method, which is a good method but limited because it cannot obtain the best-fit values of parameters. This is a manual way of calibrating the model, as opposed to the use of statistical inverse modeling where measured data is used as input into the models to provide estimates of model parameters according to mathematical and statistical theories. The PEST (Parameter ESTimation) model (Doherty, 2010), a method of statistical inverse modeling, was chosen to calibrate the DAYCENT model in this study. The purpose of the PEST is to assist in data interpretation, model calibration and predictive analysis. The first statistical inverse modeling for calibrating the DAYCENT model using PEST was reported by Rafique et al. (2013). However, the method's disadvantage is that some parameter functions and impacts in DAYCENT may be changed by PEST. For example, according to the Instruction of DAYCENT, most parameters in fix.100 file of DAYCENT cannot be adjusted (some parameters could be adjusted with very small ranges). However, in the study by Rafique et al. (2013), some of these parameters were calibrated by PEST. This may result in biased simulations. To overcome the weaknesses of using either "trial and error" or inverse modeling method alone for model calibration, we proposed an improved methodology, *i.e.*, combination of trial and error and inverse modeling using PEST called CPTE, which was described in our previous study (Mbonimpa et al., 2015a). In this study, the methodology has been first used for DAYCENT calibration, and to simulate climate change impacts on soil CO_2 fluxes.

Therefore, specific objectives of the present study were to: (i) improve the method of calibration to enhance the simulation of DAYCENT model and (ii) analyze the future long-term impacts of temperature and precipitation changes on soil surface CO_2 fluxes from Switchgrass land recently converted from cropland in South Dakota.

1. Materials and methods

1.1. Data measurements and sources

The research site was located near Bristol (45° 16′ 8.274″ N, 97° 50′ 8.9694″ W), South Dakota, USA. It was arranged into 12 plots measuring 21.3 m wide and 365.8 m long and comprised of three landscape positions: shoulder, backslope and footslope. Three N treatments (low, 0 kg N/ha; medium, 56 kg N/ha; and high, 112 kg N/ha) were applied annually during spring beginning in 2009. Switchgrass was planted on May 17, 2008 on land previously used for soybean production. A detailed description of the study site can be found in Mbonimpa et al. (2015b).

In this study, soil surface CO_2 fluxes were measured using a LI-8100 instrument (Automated Soil CO_2 Flux System) from plot number 103 which received the high N fertilizer rate and was located at the shoulder position. Soil CO_2 fluxes were monitored at 2-hr intervals for four years (2011, May 6 to November 1; 2012, April 4 to November 1; 2013, May 20 to November 13; and 2014, May 6 to October 26). The measured CO_2 flux data were converted to daily average values which include a total of 736 daily values, in which 85 were removed because the LI-8100 instrumentation misread and/or there were sudden and large unexplainable changes. Soil temperature and volumetric soil moisture content at 5-cm depth were measured with the soil temperature and moisture probes included with the LI-8100.

The daily maximum and minimum air temperature data for 2011 to 2013 were measured using a temperature sensor connected to the LI-8100 instrumentation at the research site. The precipitation data for 2011 through 2013 was measured at the study site. The daily maximum and minimum air temperature and precipitation from 1956 to 2010 and 2014 were retrieved from the nearest weather station in Webster, SD (25 km), in which precipitation from 2001 to 2010 and 2014 were retrieved from the nearest weather station in Bristol, SD (10 km). The soil bulk density and pH data were 1.37 Mg/m^3 and 8.09, respectively. The particle size distribution was 225 g/kg clay, 377 g/kg silt, and 398 g/kg sand.

1.2. Model performance evaluation and statistical analysis

The model performance was evaluated with five widely used quantitative criteria (Dai et al., 2014; Moriasi et al., 2007) that include the coefficient of determination (R^2, squared correlation coefficient), model performance efficiency (ME) (Nash and Sutcliffe, 1970), percent bias (PBIAS) (Gupta et al., 1999), and the RSR [the ratio of the root mean square error (RMSE) to SD (standard deviation of measured data)] (Singh et al., 2004). The R^2 is the most important criteria to compare default simulation with that of calibrated simulation or validated simulation, and its acceptable range is >0.50 (Santhi et al., 2001). The ME is the key variable used to evaluate the model performance. If ME >0.50, the performance is acceptable prediction. If ME is greater than 0.65 and less than 0.75, the performance is good. If ME >0.75, the model performance is very good (Moriasi et al., 2007). The third important criterion is RMSE-observations standard deviation ratio (RSR). Its range of satisfactory rating values is less than 0.70 (Moriasi et al., 2007). For the PBIAS, if its absolute value is less than 25% and greater than 15%, the performance is satisfactory, and $10\% < |PBIAS| < 15\%$ for good performance and $|PBIAS| < 10\%$ for very good (Moriasi et al., 2007). The lower the absolute value of PBIAS, the better the performance. Further, paired simulated soil CO_2 fluxes between different climate scenarios were compared using the Parallel-line method because these data were time correlated values as well as each pair values were not independent. The 0.05 of significance level of the statistical hypothesis test was used. The distributions of the datasets were tested for normality using Kolmogorov–Smirnov test. The data analyses were performed using SAS 9.3 (SAS, 2012).

1.3. *DAYCENT model calibration and validation*

The DAYCENT model stand-alone version DailyDayCent 08/17/2014 was used for simulating soil surface CO_2 fluxes in this study. The model inputs include daily precipitation and maximum and minimum temperature, soil texture, bulk density, pH, and historical land use and field and crop management. In this study, "trial and error" method was first used to calibrate DAYCENT model. In the DAYCENT model, there are 87 parameters that can be adjusted for simulating CO_2, and for this study, a total of 29 from 87 were selected based on previous literature and recommendation from model developers. The parameter values were reset on the basis of the available information for the experimental site. Then, the model was calibrated manually by adjusting values of the important parameters until the adjusted parameters improve the simulations of CO_2 fluxes. Through comparing the predicted CO_2 fluxes with those of measured values, the R^2 of 0.46, ME of 0.27, RSR of 0.85, and PBIAS of −18.02% was obtained. These values were out of their acceptable ranges. Therefore, PEST model was used to calibrate further the manually calibrated DAYCENT model (called "PEST calibrated model"). Combined PEST and DAYCENT models (called "PEST calibration" or "PEST calibrated model") were run for calibration using the most sensitive parameters (n = 44) and measured CO_2 flux data from 2011 to 2013. The calibrated modeled CO_2 fluxes ("PEST-MOD") were extracted from the outputs of the PEST calibrated model, and then PEST-MOD vs. measured CO_2 fluxes ("MEAS") were compared based on four statistical criteria which showed an improved calibration and prediction of CO_2 fluxes.

Validation of the calibrated DAYCENT was performed using (i) measured CO_2 fluxes in 2014, (ii) measured Switchgrass yields from 2009 to 2011, which were used to check the net primary productivity (NPP) that the model is predicting for this study site [It is noted that if the NPP for the site is not correct, then none of the other model outputs can be expected to be representative of the conditions at the site (Parton et al., 1998)], and (iii) soil temperature and soil moisture data measured from 2011 to 2013.

1.4. *Simulating and analyzing future soil surface CO_2 fluxes*

The PEST calibrated DAYCENT model was used to simulate CO_2 fluxes for long-term duration (2015 to 2070) based on future climate change scenarios, and then these simulated CO_2 fluxes were compared using Parallel-line method and Line charts. The future climate scenarios were created based on the method of incremental scenarios development (McCarthy, 2001). Each includes three variables: daily minimum (T_{min}(°C)) and maximum temperature (T_{max}(°C)) and precipitation (Prcp (cm)) from 2015 to 2070 based on the format of input for the DAYCENT model. The historic weather data from 1959 to 2014 were used for the observed time series to create the climate change scenarios. Based on the distribution of the observed time series (Fig. S1A), the maximum temperature followed a slightly decreased trend from 1959 to 2014 (Fig. S1A), which was stationary over time. Therefore, the maximum temperature for all scenarios was expected to increase by 0.5°C from 2015 to 2070 (total 56 years). The average increase of annual maximum temperature is 0.5/56°C. Then, T_{max} in 2015 = T_{max} in 1959 + 1 × 0.5/56°C, T_{max} in 2016 = T_{max} in 1960 + 2 × 0.5 / 56°C, T_{max} in 2017 = T_{max} in 1961 + 3×0.5/56°C, … , T_{max} in 2070 = T_{max} in 2014 + 56 × 0.5/56°C. For the minimum temperature, there was an increase of 2.38°C from 1959 to 2014 (Fig. S1A), which is non-stationary over time, therefore, the future minimum temperature for the 2015 to 2070 period could be possibly different increased trend as compared to that of 2015 to 2070 period. The increase range was expected 1°C through 3°C based on the fact of increase of 2.38°C from 1959 to 2014 and the range reported by IPCC which suggested increase in temperature roughly between 0.4°C and 2.6°C by 2060 relative to 1990 (IPCC, 2007). Within the range of 1 through 3°C, we set ten scenarios that include the minimum temperature values were increased by 1°C, 1.25°C, 1.5°C, 1.75°C, 2°C, 2.25°C, 2.38°C, 2.5°C, 2.75°C, and 3°C from 2015 to 2070. Therefore, the magnitude of the future minimum temperatures of ten scenarios is 2.38°C + ten different increases from 2015 to 2070 + the observed Tmin from 1959 to 2014, respectively. For example, for the scenario 5, its minimum temperature is increased by 2°C from 2015 to 2070, its daily minimum temperature in 2015 = 2.38°C + T_{min} in 1959 − 1 × (2.38 − 2°C) / 56, the daily T_{min} in 2016 = 2.38°C + T_{min} in 1960 − 2 × (2.38 − 2°C) / 56, the daily T_{min} in 2017 = 2.38°C + T_{min} in 1961 − 3 × (2.38 − 2°C) / 56, … , the daily T_{min} in 2070 = 2.38°C + T_{min} in 2014 − 56 × (2.38 − 2°C) / 56. Based on the same algorithm, T_{min} in other nine scenarios were calculated. Thus, the ten scenarios of temperature changes were created while Prcp was kept constant. They were named as x1, x2, …, x10, in which x7 is corresponding to +2.38°C (the amount of increase of observed minimum temperature from 1959 to 2014) and was regarded as Temperature Business As Usual (T-BAU).

The 13 scenarios of precipitation change were also created. Changes in precipitation from y1 to y13 are corresponding to −30%, −25%, −20%, −15%, −10%, −5%, 0, +5%, +10%, +15%,

+20%, +25%, and +30% of the precipitation measured for 1959 to 2014. The frequencies of precipitation for future climate scenarios were kept same to that of 1959 to 2014. However, the range is based on that reported by IPCC's projected precipitation to be approximately between -30% to 30% across the globe by 2090 relative to 1990 (IPCC, 2007). The y7 is the scenario with 0% of precipitation and was regarded as Precipitation Business As Usual (P-BAU).

2. Results

2.1. Measured CO_2 fluxes and DAYCENT calibration and validation

Soil surface CO_2 fluxes from Switchgrass land varied seasonally and yearly (Fig. 1A). The higher fluxes were observed in the summer of 2012. The CO_2 data monitored from 2011 through 2013 were used for DAYCENT model calibration to develop the DAYCENT model, and the data from 2014 were used for validation. The most sensitive parameters in DAYCENT model were identified based on the scaled sensitivity values from PEST output. Out of 87 parameters, 44 were identified to be the most sensitive to simulate soil CO_2 fluxes. These parameters were ranked in descending order based on the scaled sensitivity values presented in Supplementary data of Table 1 (*i.e.*, Table S1 in Supplementary data in Appendix A). The parameters prbmn(1_1), epnfs(2), sfavail(1), biomax, and pramn(1_1) in the DAYCENT model were observed to be the most sensitive. The prbmn (1_1) is the intercept parameter for computing minimum C/N ratio for below ground matter as a linear function of annual precipitation. Epnfs (2) is intercept value for determining the effect of annual evapotranspiration non-symbiotic soil N fixation. Sfavail (1) is species specific fraction of N available to grass/crop. Biomax is biomass level above which the minimum and maximum C/E ratios of the new shoot increments equal pramn (*, 2) and pramx (*,2) respectively. Pramn (1_1) is minimum C/N ratio with zero

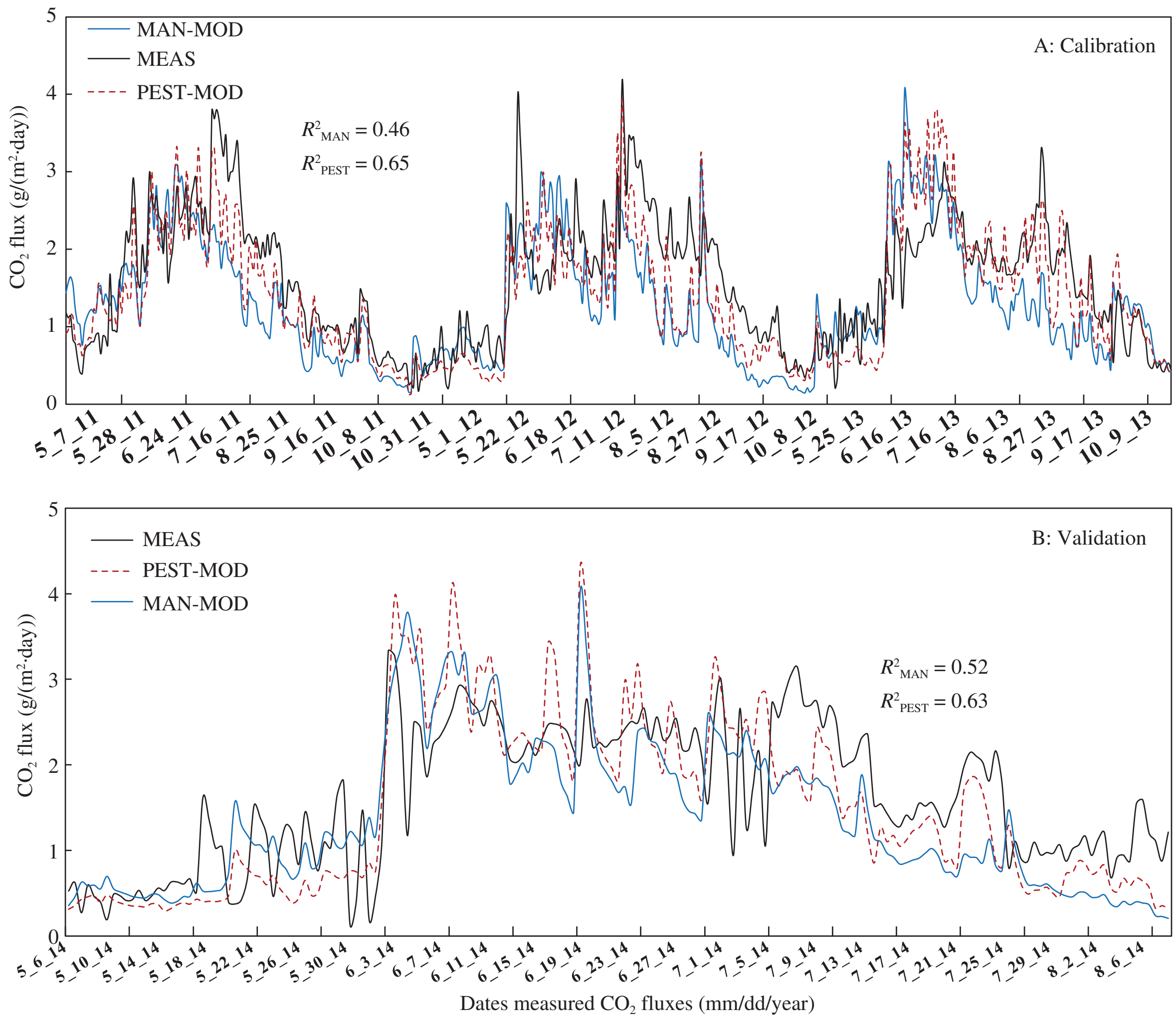

Fig. 1 – (A) Calibration: distribution of measured and modeled values of CO_2 (g/m²/day) fluxes from 2010 through 2013, (B) validation: distribution of measured and modeled values of CO_2 (g/m²/day) fluxes from 2014. MEAS, measured values; PEST-MOD, calibrated modeled CO_2 fluxes using PEST model; MAN-MOD, manually calibrated modeled CO_2 fluxes using "trial and error" method; PEST: parameter estimation.

Table 1 – Evaluation criteria for comparing soil surface CO_2 fluxes, soil temperature, and soil moisture between measured and modeled data using manually calibrated DAYCENT (Manual) and PEST calibrated DAYCENT (PEST) model for calibration and validation.

Evaluation criteria †	Calibration		Validation					
	CO_2 (g/(m^2·day))		CO_2 (g/(m^2·day))		Soil temperature (°C)		Soil moisture (cm^3/cm^3)	
	Manual	PEST	Manual	PEST	Manual	PEST	Manual	PEST
R^2 ([0.5,1))	0.46	0.65	0.52	0.63	0.86	0.86	0.60	0.62
ME ([0.5, 1))	0.27	0.56	0.31	0.40	0.49	0.41	−4.76	−5.41
RSR ([0.7, 0))	0.85	0.66	0.83	0.78	0.71	0.76	2.40	2.53
PBIAS ([25%, 0))	−18.02	−10.28	−13.92	−7.88	8.36	9.78	−33.81	−36.09

† R^2 = coefficient of determination; ME = model performance efficiency; RSR = the ratio of the root mean squared error to standard deviation of measured data; and PBIAS = percent bias.

biomass. Other 39 parameters were descripted in Table S1. Then values of the 44 parameters were adjusted for DAYCENT calibration until the adjusted parameters improve the simulations of CO_2 fluxes.

The data in Fig. 1A showed that the simulated CO_2 fluxes using the manual and DAYCENT-PEST calibration were observed similar trends with those of the measured fluxes. The data reported in Fig. 1A showed an agreement between modeled and measured soil CO_2 fluxes except for few unaligned peaks. The PEST calibrated DAYCENT (DAYCENT-PEST) provided the best prediction for CO_2 fluxes compared to manual calibration of DAYCENT. Data in Table 1 showed the evaluation criteria of model performance for calibration and validation periods for modeling CO_2 fluxes. The coefficient of determination (R^2) value of 0.65 of the PEST calibrated DAYCENT model indicated that there was a strong linear relationship between the PEST calibrated and measured CO_2 fluxes, whereas, R^2 of the manual calibrated model was 0.46 (Table 1). The percent bias (PBIAS) value of 10.28% was good for the PEST calibrated model, whereas, it was −18.02% for the manual model. Both the R^2 and the PBIAS values of the PEST calibrated DAYCENT model indicated that there was not only a strong linear relationship but there was also a very close magnitude between the DAYCENT-PEST calibrated model and measured CO_2 fluxes. Also, modeling efficiency (ME) of 0.56 of PEST calibrated model was in the acceptable range, whereas the ME value of 0.27 of the manual model was out of the range. Further, the RSR (ratio of RMSE to standard deviation (SD) of measured CO_2 fluxes) value of 0.66 for the PEST calibrated model was reasonably good for the model performance, whereas, the manually calibrated model had a RSR value of 0.85, which was out of the range of satisfactory values (<0.70). These results indicated that our final results of calibration of DAYCENT are good.

For validation, the simulated and measured CO_2 fluxes had similar trends and closer magnitude (Fig. 1B). The R^2, ME, RSR, and PBIAS values of the PEST calibrated model vs. the manually calibrated model for the validation period were 0.63 vs. 0.52, 0.40 vs. 0.31, 0.76 vs. 0.83, and −7.88% vs. −13.92, respectively. These values of R^2 and PBIAS for DAYCENT-PEST model were within satisfactory rating values compared to those of manually calibrated model (Table 1). The PEST vs. manually calibrated models simulated the soil temperature reasonably well with values for R^2, ME, RSR, and PBIAS of 0.86 vs. 0.86, 0.41 vs. 0.49, 0.76 vs. 0.71, and 9.78% vs. 8.36%. These values for simulating the soil moisture were 0.62 vs. 0.60, −5.41 vs. −4.76, 2.53 vs. 2.40, and −36.09% vs. −33.81%, respectively. Results in Fig. 2a, b showed that the simulated soil temperature data matched closely to the measured temperature. Further, modeled soil moisture content provided similar trend with the measured soil moisture but had different magnitude. For Switchgrass yield validation for the PEST calibrated model vs. the manually calibrated model, simulated yields of Switchgrass from 2009 to 2011 closely resembled the measured yields based on their PBIAS values of −1.98% vs. 0.84%, −5.19% vs. −2.50%, and −2.81% vs. 3.72% (Table 2). In general, the PEST calibrated DAYCENT model provided more satisfactory validation based on the above results, and hence was used for all the long-term climate scenarios.

2.2. CO_2 fluxes forecasts using BAU weather data

The PEST calibrated DAYCENT model along with the BAU weather data was used to simulate soil CO_2 from 2011 to 2070. The simulated annual CO_2 fluxes from Switchgrass land provided a trend of polynomial curve from 2015 to 2070 (Fig. 3a). The curve function is: $y = -0.0064x^3 + 0.4709x^2 - 2.9065x + 422.21$, where y is the annual CO_2 fluxes, x is year from 2015 to 2070. The simulated annual average value of CO_2 fluxes from 2015 to 2070 is 554.84 (g/(m^2 year)) with standard deviation of 103.68 and 95% confidence interval [527.07, 582.61].

2.3. Simulating the impacts of changing temperature scenarios on CO_2 fluxes

The PEST calibrated DAYCENT model was used to simulate yearly CO_2 fluxes from 2011 to 2070 based on different temperature scenarios, and then these fluxes were compared with the simulated CO_2 fluxes using BAU (note: the calculations of BAU weather data were described in the Materials and methods section) (Table S2). Soil CO_2 fluxes were not significantly affected by temperature increase from 1°C to 3°C in long-term (2015–2070) (Table 3). However, the annual means of simulated CO_2 fluxes provided a trend of slightly linear increase with the minimum temperature increases from 1°C to 3°C (Table 3 and Fig. 4).

The CO_2 fluxes under wet, dry and BAU were provided a trend of polynomial curves (Fig. 3b). The magnitude of fluxes under these three scenarios was narrower from 2015 to 2048.

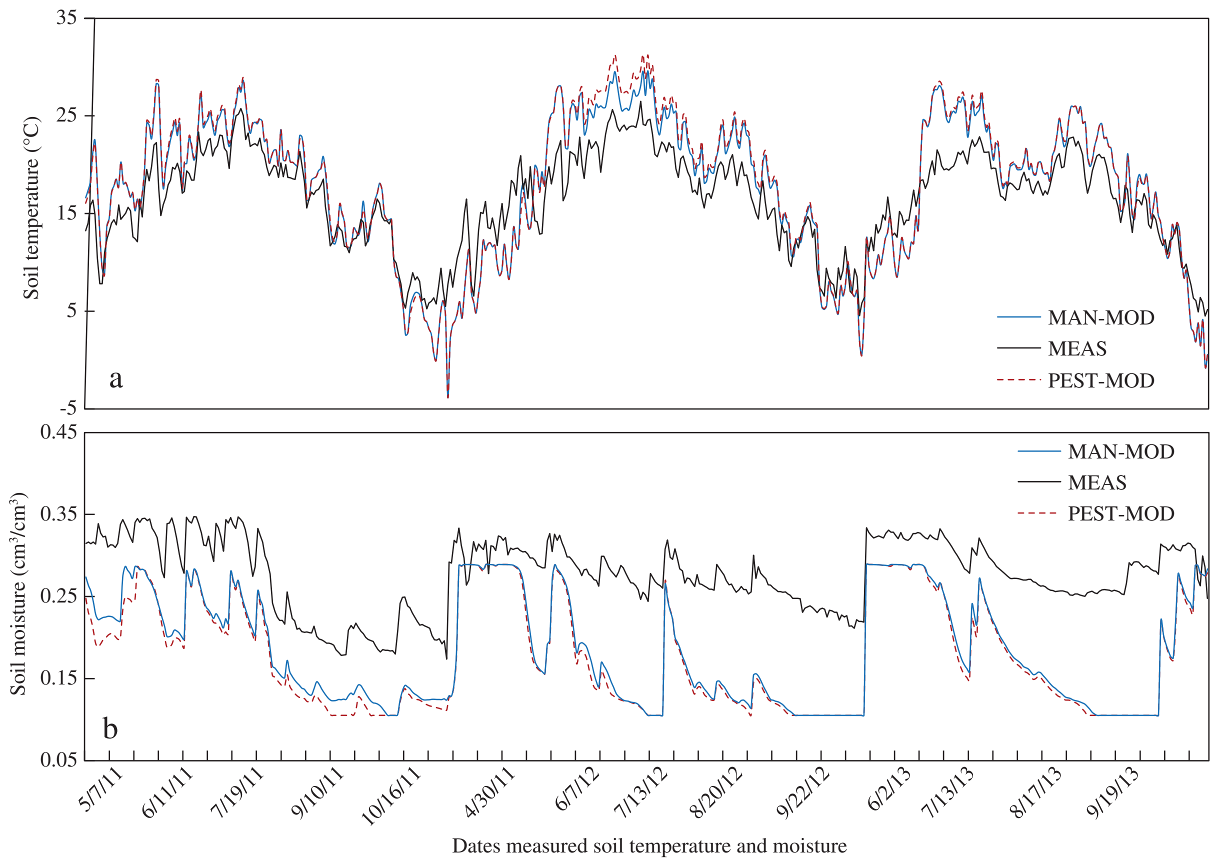

Fig. 2 – Comparison of measured and simulated soil temperature (a), and soil moisture content (b) for validation. MEAS, measured values; PEST-MOD, calibrated modeled values using PEST model; and MAN-MOD, manually calibrated modeled values using "trial and error".

However, the trend and magnitude of CO_2 fluxes for the dry condition was different from those of wet and BAU beyond 2049. These fluctuations were wider under dry conditions than that under P-BAU and wet conditions. In contrast, CO_2 fluxes had a similar trend with those of BAU but the magnitude of fluxes was lower (Fig. 3b).

Fig. 4 shows the simulated yearly mean CO_2 fluxes (g/m^2/year) corresponding to ten temperature scenarios under P-BAU, wet (+30% precipitation), and dry conditions (−30% precipitation). Under wet and P-BAU condition, the CO_2 fluxes increased slightly with the increase of temperature, whereas, these fluxes had an observable increased trend under dry condition with the increase of temperature (Fig. 4). The CO_2 fluxes under wet condition were less than those of dry conditions and P-BAU (Fig. 4). The soil CO_2 fluxes from Switchgrass land in January, February, March, and December were very low, whereas, these fluxes were the highest in July. The mean CO_2 fluxes under wet condition from May to October were less than that under P-BAU and drought conditions, which were of similar trends and magnitudes (Fig. S2). The trends of monthly soil CO_2 fluxes were of similar trends of monthly temperature and precipitation (Fig. S2 and S4). Further, rates of monthly soil CO_2 fluxes based on scenarios of temperature changes were compared under P-BAU, wet, and drought conditions (Table S4). Comparing to the P-BAU and dry condition during the growing season from April to November, monthly rates of CO_2 fluxes under wet condition were negative and the rates in June and October were the highest. However, monthly rates of CO_2 fluxes under drought condition had different magnitudes of these rates, and lower than that under wet and P-BAU conditions (Table S4).

Table 2 – Comparison of modeled and measured Switchgrass yield (g/(m^2·year)) for validation.

Year	Measured	DAYCENT-PEST		DAYCENT	
		Modeled	PBIAS (%)	Modeled	PBIAS (%)
2009	303.88	297.87	−1.98	300.37	0.84
2010	566.69	537.30	−5.19	523.87	−2.50
2011	545.21	529.89	−2.81	549.61	3.72

2.4. Simulating the impacts of changing precipitation scenarios on CO_2 fluxes

The precipitation increase from +20% to +30% significantly impacted CO_2 fluxes compared to those from P-BAU ($p < 0.05$), however, precipitation changes from −30% to +15% did not impact soil CO_2 fluxes ($p > 0.05$) (Table 4).

The mean CO_2 fluxes with 1°C increase in temperature were slightly lower than those under temperature with BAU (T-BAU) condition (Fig. 5). However, a precipitation increase along with a 1°C increase in temperature resulted in slightly

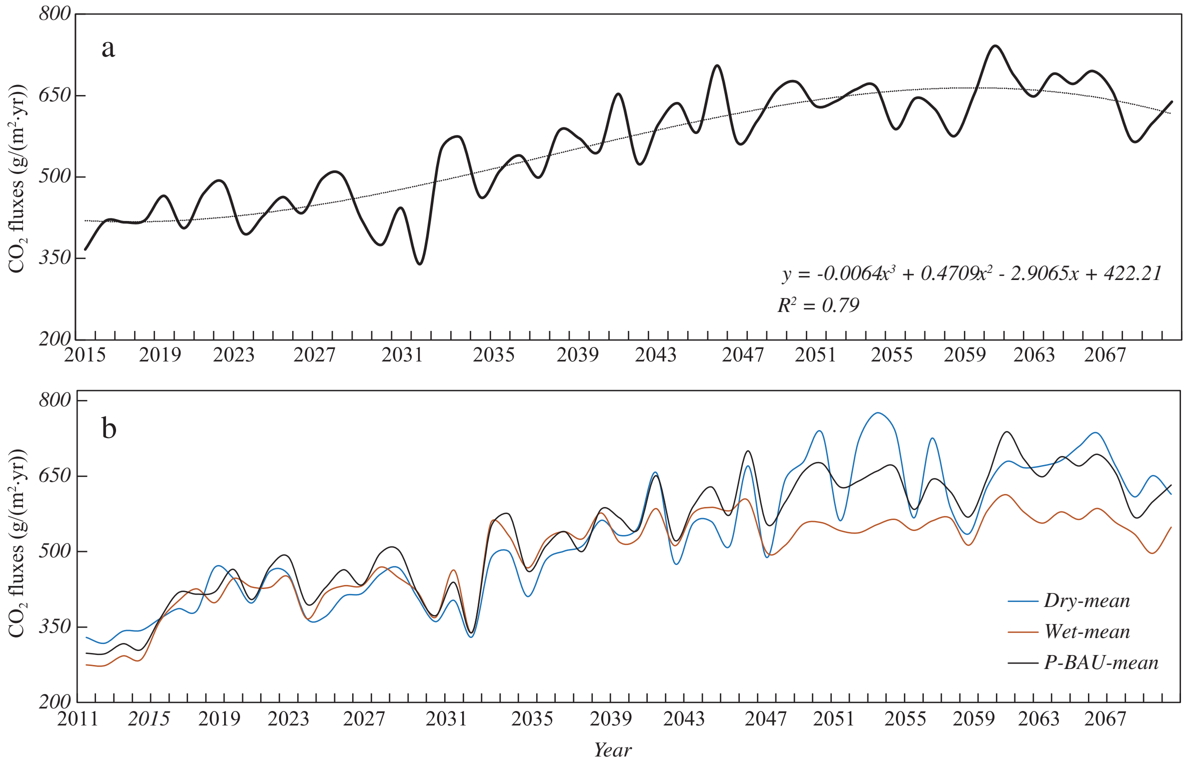

Fig. 3 – Average annual simulated CO_2 fluxes from 2015 to 2070 simulated using (a) the weather data of BAU and (b) temperature scenarios from 2011 to 2070 under dry, wet, and P-BAU conditions. P-BAU: Precipitation Business As Usual; BAU: Business As Usual.

elevated soil CO_2 fluxes (Fig. 6). Under T-BAU and +1°C condition, the CO_2 fluxes had similar trends with a 2-degree polynomial curve. The data also showed that with the increase in precipitation from −30% to +30%P, the CO_2 fluxes increased initially with decreased precipitation, peaked at an optimal precipitation, and then decreased to the lowest point under wet condition or increased precipitation (30%P) (Fig. 6). For the T-BAU trend, the maximum CO_2 fluxes were observed with −15%P and the trend function was given by: $y = -295.14x^2 - 78.277x + 539$, whereas, the maximum CO_2 fluxes with the +1°C temperature were observed with −5%P, and the trend function was given by: $y = -309.7x^2 - 52.764x + 531.59$ (Fig. 6). The soil CO_2 fluxes from Switchgrass land in January, February, March, and December were very low, whereas, these fluxes were the highest in July. The mean CO_2 fluxes under T-BAU from May to October were slightly greater than that under +1°C condition (Fig. S3). The trends of the monthly soil CO_2 fluxes were of similar trends of monthly temperature and precipitation (Figs. S3 and S4). Further, rates of monthly soil CO_2 fluxes based on scenarios of precipitation changes were compared under T-BAU and +1°C conditions. All of 12 monthly rates of CO_2 fluxes under T-BAU condition were positive, in which November has the biggest rate of 4.06% and June has the least rate of 0.39% (Table S4).

Table 3 – Statistical results of comparing simulated future soil CO_2 fluxes (g/(m^2·year)) based on different temperature scenarios.

CO_2 fluxes — temperature changes					
Var[a]	Mean ± SD	L95%CI	U95%CI	*p*-Value[b]	
x1	533.19 ± 115.33	503.40	562.98	x1/x7:0.63	–
x2	533.00 ± 115.33	503.21	562.80	x2/x7:0.62	x2/x1:0.99
x3	532.51 ± 115.26	502.74	562.29	x3/x7:0.59	x3/x2:0.96
x4	535.61 ± 117.44	505.27	565.94	x4/x7:0.81	x4/x3:0.77
x5	536.21 ± 117.16	505.94	566.47	x5/x7:0.85	x5/x4:0.95
x6	536.99 ± 117.81	506.56	567.43	x6/x7:0.91	x6/x5:0.94
x7	538.15 ± 118.28	507.60	568.71	–	x7/x6:0.91
x8	538.48 ± 118.50	507.87	569.09	x8/x7:0.97	x8/x7:0.89
x9	540.50 ± 119.34	509.67	571.33	x9/x7:0.82	x9/x8:0.85
x10	540.97 ± 119.72	510.04	571.90	x10/x7:0.79	x10/x9:0.96

[a] x1 = +1°C; x2 = +1.25°C; x3 = +1.5°C; x4 = +1.75°C; x5 = +2°C; x6 = +2.25°C; x7 = +2.38°C; x8 = +2.5°C; x9 = +2.75°C; x10 = +3°C.
[b] *p*-Values were from output of Parallel-line analysis.

3. Discussion

Our previous study at this site concluded that climate impacted the soil surface CO_2 fluxes (Mbonimpa et al., 2015b). However, to assess the potential climate change impacts on these fluxes in long-term was still a researchable question. This study showed that the CO_2 fluxes from Switchgrass land provided increased trends from 2011 to 2070 using a range of different climate scenarios (Fig. 3a, b, and Fig. 5). These trends, however, were not a linear increase with the years but rather a polynomial. The latter trend resulted from interactions of the multiple factors that were influenced by climate. The temperature and precipitation

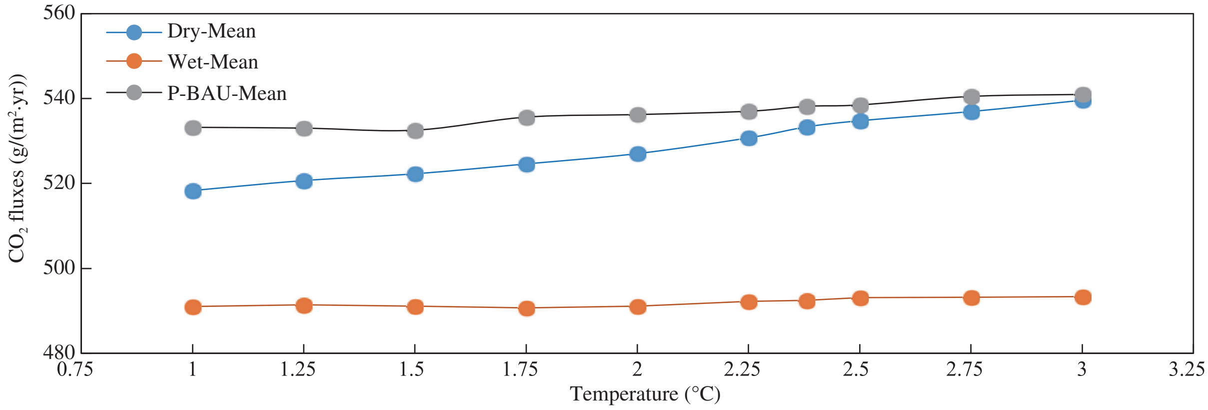

Fig. 4 – Average annual simulated CO_2 fluxes corresponding to temperature scenarios +1 through +3°C under dry, wet, and P-BAU conditions. P-BAU: Precipitation Business As Usual.

directly determine level of soil temperature and moisture, respectively, which are the most important abiotic parameters determining CO_2 fluxes and its underlying processes (Kutsch et al., 2009; Subke and Bahn, 2010). Further, the future 56 years forecasting of CO_2 fluxes were predicted with 95% confidence interval for mean based on different climate scenarios (Table S2). These findings can be useful in developing greenhouse gas mitigation strategies.

Results from this study also showed that annual CO_2 fluxes were not significantly different for all the temperature scenarios (Table 3). These fluxes slightly increased with the increase in temperature (Fig. 4). Similarly, CO_2 fluxes with 13 precipitation scenarios were also not significantly different except for three scenarios (+20%, +25%, and +30%P), which resulted in lower CO_2 fluxes (Table 4 and Fig. 6). These data indicated that impacts of long-term temperature and precipitation changes on respiration of CO_2 under local conditions were not significant. It has been reported in various studies that perennial grassland improves soil carbon sequestration and emit less emissions from soils. This may be one of reasons why long-term climate change impacts on CO_2 fluxes can be minimal on Switchgrass land. However, further long-term research is needed to support this statement.

Table 4 – Statistical results of comparing simulated future soil CO_2 fluxes (g/(m²·year)) based on different precipitation scenarios.

CO_2 fluxes — precipitation changes					
Var [a]	Mean ± SD	L95%CI	U95%CI	*p*-Value [b]	
y1	533.30 ± 133.60	498.79	567.82	y1/y7:0.53	–
y2	538.97 ± 134.66	504.18	573.75	y2/y7:0.86	y2/y1:0.65
y3	545.53 ± 139.66	509.45	581.61	y3/y7:0.78	y3/y2:0.65
y4	547.12 ± 136.34	511.90	582.34	y4/y7:0.64	y4/y3:0.85
y5	544.42 ± 130.76	510.64	578.20	y5/y7:0.75	y5/y4:0.88
y6	543.38 ± 125.84	510.87	575.88	y6/y7:0.75	y6/y5:0.99
y7	538.15 ± 118.28	507.60	568.71	–	y7/y6:0.75
y8	534.12 ± 113.73	504.74	563.50	y8/y7:0.78	y8/y7:0.78
y9	526.26 ± 106.28	498.80	553.71	y9/y7:0.4	y9/y8:0.58
y10	519.39 ± 100.53	493.42	545.36	y10/y7:0.18	y10/y9:0.62
y11	509.93 ± 96.56	484.98	534.87	y11/y7:0.039	y11/y10:0.44
y12	499.73 ± 93.36	475.61	523.85	y12/y7:0.004	y12/y11:0.40
y13	492.48 ± 89.24	469.42	515.53	y13/y7<0.001	y13/y12:0.56

[a] y1 = −30%P; y2 = −25%P; y3 = −20%P; y4 = −15%P; y5 = −10%P; y6 = −5%P; y7 = 0%P; y8 = 5%P; y9 = 10%P; y10 = 15%P; y11 = 20%P; y12 = 25%P; y13 = 30%P.
[b] *p*-Values were from output of Parallel-line analysis.

Soil CO_2 fluxes under simulated drought conditions (−30%P) exhibited wider fluctuations in the long-term (2011–2070) (Fig. 3b). Some studies have shown that soil moisture affects CO_2 fluxes by its direct influence on root and microbial activities, and indirect influences on soil physical and chemical properties (Raich and Schlesinger, 1992; Schimel and Clein, 1996). Drought conditions reduce soil respiration and wetter conditions increase CO_2 production (Jensen et al., 2003; Mbonimpa et al., 2015b). The heterotrophic respiration is more susceptible to drought than autotrophic respiration (Scott-Denton et al., 2006; Zhou et al., 2007). Thus, a wide range of fluctuations in CO_2 fluxes under drought condition were observed compared to those under P-BAU (Fig. 3b). Furthermore, the CO_2 fluxes exhibited the slopes of increased trend with increasing temperature from 1°C through 3°C. These slopes were lower under P-BAU and wet condition compared to that with dry condition (Fig. 4). This may be due to the fact that Switchgrass performs better under soil water deficits. The present study site is located under the humid continental climate which is still appropriate for Switchgrass to grow well even if the precipitation amount were reduced by 30% compared to the P-BAU. Furthermore, the cultivar of Switchgrass for the study site was developed for local conditions. The improved Switchgrass growth could increase the respiration of CO_2 with temperature under dry conditions compared to that under wet conditions. However, under wet conditions, higher water content in soils decreased air-filled porosity, increased stomatal resistance and hence decreased CO_2 respiration (Kirkham, 2011).

These results also indicated that when temperature is kept constant, both dry and wet conditions could decrease CO_2 emissions (Fig. 6). Some studies have shown that there is a negative effect of elevated soil temperature on soil moisture due to increased evapotranspiration (Liu et al., 2009; Poll et al., 2013; Shaver et al., 2000). Additionally, it is not necessarily true that precipitation always increases moisture content of the soils probably because most precipitation events were

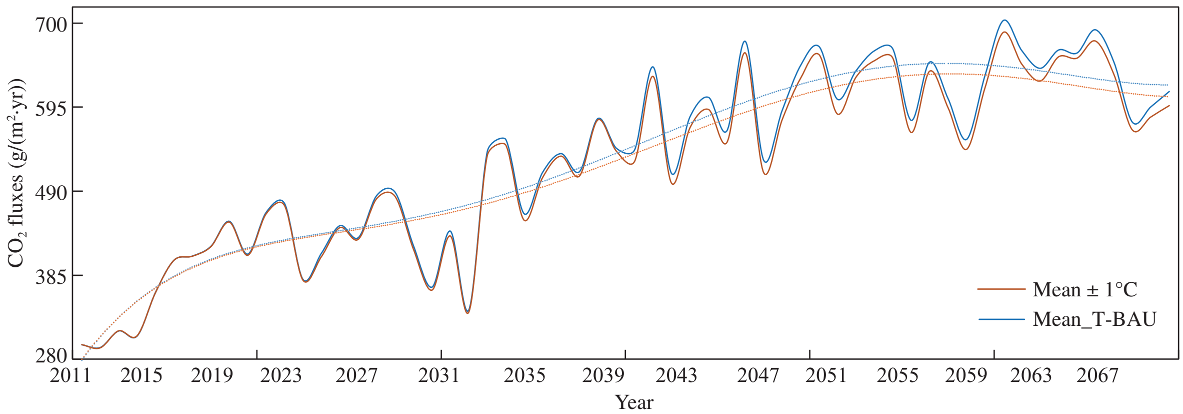

Fig. 5 – Trends of simulated average annual CO_2 fluxes from 2011 to 2070 based on precipitation changes from −30% to +30% under temperature of BAU (increase of 2.38°C) and increase of 1°C with years.

unlikely to rewet the soil to a greater depth (Poll et al., 2013). The reduction in soil moisture by soil warming was shown to reduce microbial respiration in a dry semiarid temperate steppe (Liu et al., 2009). This inconsistency between soil moisture and soil respiration is probably due to the above mentioned inability of precipitation events to rewet the dry soil to a depth of 15 cm (Poll et al., 2013), especially, at the shoulder position as is the case in our research site. Under moisture excess or waterlogged conditions, there were anaerobic conditions and suppression of CO_2 emissions (Liu et al., 2002). Furthermore, higher water content in soils is a condition attributed to reduced transpiration due to increased stomatal resistance (Kirkham, 2011). These conditions could result in lack of oxygen in soil organic matter, which subsequently decreases respiration. Therefore, the CO_2 fluxes were lower in wet conditions compared to dry and BAU.

Soil surface CO_2 fluxes were higher with the T-BAU (+2.38°C) compared to that with +1°C condition (Fig. 6). This was primarily because temperature increased CO_2 emissions with increased soil organic matter decomposition. Further, precipitation amount contributing to the maximum CO_2 flux under T-BAU was lower than that under +1°C condition (Fig. 6). This might be explained by higher temperature values that can reduce soil moisture content through the evaporation process and increasing decomposition of organic compounds in aerobic soils. Further, the humid continental climate at the study site could result in the maximum CO_2 fluxes under the reduced precipitation conditions, indicating that properly managed Switchgrass in the present site has the potential to mitigate CO_2 fluxes. Data from this study showed that increased precipitation with increased temperature produced higher CO_2 fluxes. These findings were also supported by other researchers who reported that the main driving factors affecting belowground soil respiration were temperature, precipitation or temperature in combination with precipitation (Do, 2008). The interactions of soil temperature and moisture determine soil respiration in most ecosystems (Kanerva et al., 2007; Li et al., 2006). Regression analysis showed that soil moisture positively affected the correlation between soil temperature and soil respiration and explained 25% of the variation in Q10 values (Poll et al., 2013). The increase in CO_2 fluxes under higher temperature condition may be explained by increased plant biomass in general and subsequent increases in C flow to the soil with increase of temperature and precipitation (Kanerva et al., 2007).

4. Conclusions

Soil surface CO_2 fluxes are strongly influenced by climate, however, evaluating impacts of different climate scenarios on

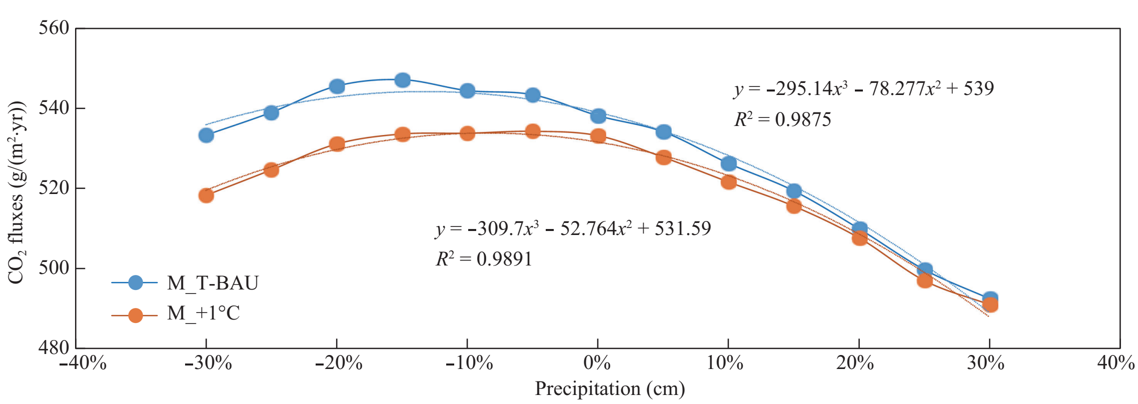

Fig. 6 – Trends of simulated average annual CO_2 fluxes from 2011 to 2070 based on precipitation changes from -30% to +30% under temperature of BAU (increase of 2.38°C) and increase of 1°C with changing precipitation. BAU: Business As Usual.

these fluxes in long-term is difficult without modeling tools. Our previous study that included measured CO_2 data for 3 years showed that climate significantly impacted the CO_2 fluxes. Therefore, this study was conducted to assess the long-term impacts of climate on CO_2 fluxes from Switchgrass land recently converted from cropland. DAYCENT model was used for assessing the climate change scenarios. The calibration of this model was improved using a new (CPTE) methodology that combines the "trial and error" and PEST model to reduce the biasness of model predictions. The four data (CO_2 fluxes of 2014, Switchgrass yield from 2009 to 2011, and soil temperature and soil moisture from 2011 to 2013) were used for validating the model. Then the calibrated and validated DAYCENT model was used to simulate and analyze future CO_2 fluxes.

This study concluded that measured soil CO_2 fluxes were higher for 2012 which was a drought year, and these fluxes when simulated for long-term (2015–2070) provided an increased pattern of polynomial curve. Soil surface CO_2 fluxes from Switchgrass land showed an increasing trend from 2011 to 2070 with a polynomial curve. The distribution patterns of temperature and precipitation were more important for soil CO_2 efflux seasonal dynamics. Our simulation results showed that the future CO_2 emissions from Switchgrass land in South Dakota would generally be insignificantly different with changes in temperature and precipitation, therefore, Switchgrass grown for longer durations could reduce changes in CO_2 fluxes from soil as a result of temperature and precipitation changes within the ranges of the climate scenarios to some extent. However, to assess the climate change impacts based on just one parameter was not sufficient, therefore, the future work should include a systematical analysis of different parameters such as greenhouse gas (GHG) fluxes, soil organic carbon, total nitrogen and other crops and soil data from Switchgrass land.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jes.2015.08.019.

REFERENCES

Adler, P.R., Del Grosso, S.J., Parton, W.J., 2007. Life-cycle assessment of net greenhouse-gas flux for bioenergy cropping systems. Ecol. Appl. 17 (3), 675–691.

Chamberlain, J.F., Miller, S.A., Frederick, J.R., 2011. Using DAYCENT to quantify on-farm GHG emissions and N dynamics of land use conversion to N-managed switchgrass in the Southern U.S. Agric. Ecosyst. Environ. 141 (3-4), 332–341.

Dai, Z., Birdsey, R.A., Johnson, K.D., Dupuy, J.M., Hernandez-Stefanoni, J.L., Richardson, K., 2014. Modeling carbon stocks in a secondary tropical dry forest in the Yucatan Peninsula, Mexico. Water Air Soil Pollut. 225 (4), 1–15.

Davis, S.C., Parton, W.J., Dohleman, F.G., Smith, C.M., Del Grosso, S., Kent, A.D., et al., 2010. Comparative biogeochemical cycles of bioenergy crops reveal nitrogen-fixation and low greenhouse gas emissions in a *Miscanthus* × *giganteus* agro-ecosystem. Ecosystems 13 (1), 144–156.

De Gryze, S., Wolf, A., Kaffka, S.R., Mitchell, J., Rolston, D.E., Temple, S.R., et al., 2010. Simulating greenhouse gas budgets of four California cropping systems under conventional and alternative management. Ecol. Appl. 20 (7), 1805–1819.

Do, D., 2008. The Effects of Temperature and Precipitation on Carbon Dioxide Flux from California Grassland Soil. pp. 1–14.

Doherty, J.E., 2010. PEST, Model-Independent Parameter Estimation—User Manual. Watermark Numerical Computing, Brisbane.

Gupta, H.V., Sorooshian, S., Yapo, P.O., 1999. Status of automatic calibration for hydrologic models: comparison with multilevel expert calibration. J. Hydrol. Eng. 4 (2), 135–143.

Jensen, K.D., Beier, C., Michelsen, A., Emmett, B.A., 2003. Effects of experimental drought on microbial processes in two temperate heathlands at contrasting water conditions. Appl. Soil Ecol. 24 (2), 165–176.

Kanerva, T., Regina, K., Rämö, K., Ojanperä, K., Manninen, S., 2007. Fluxes of N_2O, CH_4 and CO_2 in a meadow ecosystem exposed to elevated ozone and carbon dioxide for three years. Environ. Pollut. 145 (3), 818–828.

Kirkham, M.B., 2011. Elevated Carbon Dioxide: Impacts on Soil and Plant Water Relations. CRC Press, Boca Raton, Fl, USA.

Kutsch, W.L., Bahn, M., Heinemeyer, A., 2009. Soil Carbon Dynamics: An Integrated Methodology. Cambridge University Press, Cambridge.

Lewandowski, I., Scurlock, J.M.O., Lindvall, E., Christou, M., 2003. The development and current status of perennial rhizomatous grasses as energy crops in the US and Europe. Biomass Bioenergy 25 (4), 335–361.

Li, Y.Q., Xu, M., Zou, X.M., 2006. Heterotrophic soil respiration in relation to environmental factors and microbial biomass in two wet tropical forests. Plant Soil 281 (1-2), 193–201.

Liu, X.Z., Wan, S.Q., Su, B., Hui, D.F., Luo, Y.Q., 2002. Response of soil CO_2 efflux to water manipulation in a tallgrass prairie ecosystem. Plant Soil 240 (2), 213–223.

Liu, W.X., Zhang, Z., Wan, S.Q., 2009. Predominant role of water in regulating soil and microbial respiration and their responses to climate change in a semiarid grassland. Glob. Chang. Biol. 15 (1), 184–195.

Mbonimpa, E.G., Gautam, S., Lai, L., Kumar, S., Bonta, J.V., Wang, X., et al., 2015a. Combined PEST and trial–error approach to improve APEX calibration. Comput. Electron. Agric. 114, 296–303.

Mbonimpa, E., Hong, C.O., Owens, V.N., Lehman, R.M., Osborne, S.L., Schumacher, T.E., Clay, D.E., Kumar, S., 2015b. Nitrogen fertilizer and landscape position impacts on CO_2 and CH_4 fluxes from a landscape seeded to switchgrass. GCB Bioenergy 7 (4), 836–849.

McCarthy, J.J., 2001. Climate Change 2001: Impacts, Adaptation, and Vulnerability: Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.

McLaughlin, S.B., Kiniry, J.R., Taliaferro, C.M., De La Torre Ugarte, D., 2006. Projecting yield and utilization potential of switchgrass as an energy crop. Adv. Agron. 90, 267–297.

Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.L., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50 (3), 885–900.

Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I—a discussion of principles. J. Hydrol. 10 (3), 282–290.

Parrish, D.J., Fike, J.H., 2005. The biology and agronomy of switchgrass for biofuels. Crit. Rev. Plant Sci. 24 (5-6), 423–459.
Parton, W.J., 1996. The CENTURY model. In: Powlson, D.S., Smith, P., Smith, J.U. (Eds.), Evaluation of Soil Organic Matter Models. Springer, Berlin, pp. 283–291.
Parton, W.J., Schimel, D.S., Cole, C.V., Ojima, D.S., 1987. Analysis of factors controlling soil organic matter levels in Great Plains grasslands. Soil Sci. Soc. Am. J. 51 (5), 1173–1179.
Parton, W.J., Hartman, M., Ojima, D., Schimel, D., 1998. DAYCENT and its land surface submodel: description and testing. Glob. Planet. Change 19 (1-4), 35–48. http://dx.doi.org/10.1016/S0921-8181(98)00040-X.
Poll, C., Marhan, S., Back, F., Niklaus, P.A., Kandeler, E., 2013. Field-scale manipulation of soil temperature and precipitation change soil CO_2 flux in a temperate agricultural ecosystem. Agric. Ecosyst. Environ. 165, 88–97.
Rafique, R., Fienen, M.N., Parkin, T.B., Anex, R.P., 2013. Nitrous oxide emissions from cropland: a procedure for calibrating the DayCent biogeochemical model using inverse modelling. Water Air Soil Pollut. 224 (9), 1677. http://dx.doi.org/10.1007/S11270-013-1677-Z.
Raich, J.W., Schlesinger, W.H., 1992. The global carbon dioxide flux in soil respiration and its relationship to vegetation and climate. Tellus B 44 (2), 81–99.
Santhi, C., Arnold, J.G., Williams, J.R., Dugas, W.A., Srinivasan, R., Hauck, L.M., 2001. Validation of the swat model on a large river basin with point and nonpoint sources. JAWRA 37 (5), 1169–1188.
SAS, 2012. SAS Institute. The SAS System for Windows. Release 9.3. SAS Inst., Cary, NC, USA.
Schimel, J.P., Clein, J.S., 1996. Microbial response to freeze–thaw cycles in tundra and taiga soils. Soil Biol. Biochem. 28 (8), 1061–1066.
Scott-Denton, L.E., Rosenstiel, T.N., Monson, R.K., 2006. Differential controls by climate and substrate over the heterotrophic and rhizospheric components of soil respiration. Glob. Chang. Biol. 12 (2), 205–216.
Shaver, G.R., Canadell, J., Chapin, F.S., Gurevitch, J., Harte, J., Henry, G., et al., 2000. Global warming and terrestrial ecosystems: a conceptual framework for analysis. Bioscience 50 (10), 871–882.
Singh, J., Knapp, H.V., Demissie, M., 2004. Hydrologic modeling of the Iroquois River watershed using HSPF and SWAT ISWS CR 2004-08 Illinois State Water Survey, Champaign, Ill.
Smith, P., Smith, J.U., Powlson, D.S., McGill, W.B., Arah, J.R.M., Chertov, O.G., et al., 1997. A comparison of the performance of nine soil organic matter models using datasets from seven long-term experiments. Geoderma 81 (1-2), 153–225.
Subke, J.A., Bahn, M., 2010. On the 'temperature sensitivity'of soil respiration: can we use the immeasurable to predict the unknown? Soil Biol. Biochem. 42 (9), 1653–1656.
Wright, L., 2007. Historical Perspective on How and Why Switchgrass Was Selected As a "Model" High-potential Energy Crop. Bioenergy Resources and Engineering Systems, Oak Ridge, TN ORNL/TM-2007/109.
Zhou, X.H., Wan, S.Q., Luo, Y.Q., 2007. Source components and interannual variability of soil CO_2 efflux under experimental warming and clipping in a grassland ecosystem. Glob. Chang. Biol. 13 (4), 761–775.